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Does bank branch density reduce income inequality in the Spanish provinces?

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ABSTRACT

This paper analyzes whether the density of bank branches is affecting income inequality in the Spanish provinces in the post-crisis years (2015–2019). The results show a non-significant impact for the analyzed period, and hold for a variety of scenarios, estimation methods and different types of bank. Then, although most previous literature suggests that bank branches reduce inequality, especially in advanced economies, that finding does not hold for the Spanish case. The advance of digitalization and the emergence of new forms of banking are potential candidates that might explain our results.

1. Introduction

The restructuring process of the banking sector that followed the Great Recession of 2008 triggered the closure of a large number of bank branches in Europe. The Spanish case is of particular interest since, according to the Banking Structural Financial Indicators of the European Central Bank, branch closures in Spain reached 47% in the period 2008–2019, 16 percentage points above the Euro area average (31%).[1] This has dramatically reduced branch density, generating situations of financial exclusion in some areas (Maudos, 2017; Martin-Oliver, 2019). However, the reduction in branch density has been uneven across Spanish provinces, and its effects on important aspects such as income inequality are virtually unexplored, especially at the subnational level and for the post-crisis period.

A reduced density of branches can exacerbate inequality in areas with limited alternatives for credit accessibility. The importance of physical branches is supported by arguments such as proximity and access to soft information, which can ultimately condition credit availability (Nguyen, 2019). Credit constraints might have a notable impact on investment and the development of new ideas that can be detrimental for productivity and, ultimately, income per capita (Diallo and Al-Titi, 2017). Moreover, the benefits of having access to financial services on income inequality are especially noticeable for poor households and entrepreneurs (Galor and Zeira, 1993).

However, whereas physical branches were essential to access financial services until the recent past, there are nowadays other alternatives linked to the recent development of financial technologies (FinTech) and online banking, particularly in advanced countries such as Spain. Demir et al. (2022) find that FinTech is reducing income inequality, especially in high-income countries. A

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[1] Branch closures have been present in all Euro area countries, but with much lower intensity. For instance, closures reached 32% in Germany, 29% in Italy and only 9% in France.

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Table 1
Descriptive statistics.

	Obs.	Mean	Std. Dev.	Minimum	Maximum
Gini index	239	29.757	1.655	26.272	34.572
Branches	250	68.973	22.589	32.086	141.076
Commercial banks branches	250	22.644	6.976	10.495	40.549
Savings banks branches	250	32.827	12.062	13.128	67.895
Cooperative banks branches	250	13.502	13.644	0.087	56.361
Credit per capita	250	19.219	6.850	9.870	56.797
Population growth	250	−0.002	0.007	−0.017	0.018
Population density	250	129.513	168.580	8.590	829.959
log(GDP pc)	250	10.017	0.197	9.689	10.463
log(Human capital)	250	2.378	0.055	2.232	2.524
Population age	250	44.075	2.650	39.270	50.680
Internet use	250	82.685	5.290	71.900	95.000
Agriculture share	250	0.074	0.055	0.001	0.309
Industry share	250	0.162	0.063	0.040	0.317
Unemployment	250	0.176	0.063	0.072	0.383

key channel is the facilitation of financial inclusion, which fosters rural entrepreneurship. Also, digitalization of payments reduces administrative costs and corruption, leaving more resources available for social spending. Nevertheless, the support to the so-called "death of distance" is far from general. For instance, Chakravarty (2006) and Petersen and Rajan (2002) argue that advances in digital banking reduce the negative impact of branch closures only partially. More recent studies conclude that physical branches are still of great importance for credit provision to low-income households and small firms (Nguyen, 2019; Bonfim et al., 2021). The empirical evidence for different geographical contexts generally suggests that bank branches reduce inequality, especially in high-income areas (see Altunbaş and Thornton, 2019; D'Onofrio et al., 2019; Valdebenito and Pino, 2022). Accordingly, the hypothesis to be tested is:

H1: Higher branch density is associated to lower income inequality.

In order to test whether this hypothesis holds for the Spanish provinces, this study provides some evidence on the impact of bank branches on intra-regional income inequality, measured by the Gini index. It distinguishes by different types of bank and considers the post-crisis years (2015–2019), which is a more recent period than the ones used in the previous literature. Online financial services have skyrocketed in recent times, and it is then important to analyze the role of bank branches in this new context and in a country where internet access is generalized and show little regional disparities.[2]

After this introduction, Section 2 presents the empirical framework. Section 3 provides the results, and Section 4 concludes.

2. Empirical framework

The sample comprises 50 Spanish provinces (NUTS-3 in European terminology)[3] and years 2015–2019. Provinces are small enough to capture particular socio-economic environments, but are at the same time large enough to represent meaningful economic areas. As for the temporal period, year 2015 is the first one for which information on inequality is provided at the province level. Besides, although year 2020 could be included (it is the last year with data availability at the time of writing), the extremely especial conditions of that year due to the Covid-19 Pandemic make advisable to leave 2020 out the analysis, as it could generate substantial noise and one extra year does not represent a meaningful extension of our period.

Income inequality is measured by the Gini index, provided by the Spanish Bureau of Statistics (INE). Bank branch density ($Branches$) is measured by the number of branches per 100,000 inhabitants, and the information comes from the yearbooks of the Asociación Española de Banca (AEB), Confederación Española de Cajas de Ahorros (CECA) and Unión Nacional de Cooperativas de Crédito (UNACC). Different types of bank are considered, including commercial, savings and cooperative banks. As control variables, we include GDP per capita (constant euros of 2015, in logs), population growth (%), population density (inhabitants per km^2), average population age (years), unemployment (%), internet users (% of people aged 16–74 that used the internet in the last three months),[4] share of employment in agriculture (%), share of employment in industry (%), all retrieved from INE, private credit per capita (thousands of euros), provided by the Bank of Spain, and human capital (years of education of the labor force, in logs), provided by the Valencian Bureau of Economic Research (IVIE).

Some descriptive statistics are reported in Table 1, whereas Fig. 1 displays maps for the variables of interest, showing remarkable regional disparities. The first panel shows that inequality is generally higher in Madrid and in the provinces along the Mediterranean coast. Interestingly, in these regions the density of bank branches is considerably lower, as shown by the second panel. However, this pattern cannot be generalized, as there are several provinces characterized by high inequality and low branch density or the

[2] According to the Spanish Bureau of Statistics, 90.4% of the households had internet access in 2019, with a regional (Comunidades Autónomas, NUTS-2 level) standard deviation of 2.8%. These figures were 78.2% and 3.7%, respectively, in 2015, thus indicating a fast increase in coverage and a reduction of the regional gap. Unfortunately, this information is not provided at the province level (Provincias, NUTS-3 level).

[3] The Autonomous Cities of Ceuta and Melilla are excluded. Also, information on inequality levels is missing for the provinces of Navarra and País Vasco.

[4] Due to data constraints, the NUTS-2 level values have been assigned to all the corresponding NUTS-3 areas in that region.

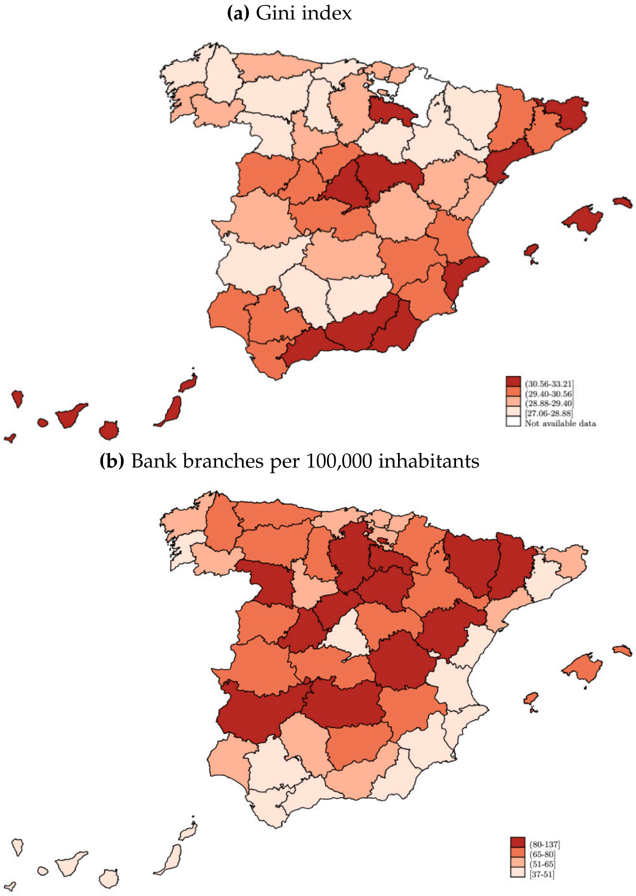

Fig. 1. Average Gini index and bank branches in the Spanish provinces (2015–2019)

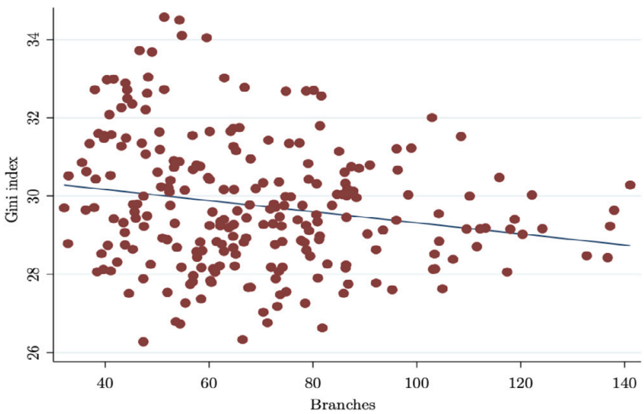

Fig. 2. The link between bank branches and the Gini index (2015–2019).

Table 2
Baseline results.

	Dependent variable: Gini index					
	Model 1 (OLS)	Model 2 (OLS)	Model 3 (OLS)	Model 4 (OLS)	Model 5 (2SLS)	Model 6 (GMM)
Branches	−0.0268*	−0.0087			−0.0161	−0.0269
	(0.0149)	(0.0143)			(0.0270)	(0.0210)
Branches growth			0.5961			
			(0.8510)			
Branches (lagged)				−0.0078		
				(0.0125)		
Credit per capita	0.0387	0.0395	0.0345	0.0380	0.0422	0.2675*
	(0.0271)	(0.0264)	(0.0257)	(0.0258)	(0.0277)	(0.1344)
Population growth	−39.2927***	−22.9880**	−21.3157**	−22.5354**	−24.0625**	30.8456
	(9.2853)	(10.4607)	(10.4131)	(10.0605)	(10.4394)	(54.2233)
Population density	−0.0206*	−0.0154	−0.0175	−0.0166	−0.0143	−0.0089**
	(0.0113)	(0.0106)	(0.0105)	(0.0107)	(0.0111)	(0.0042)
log(GDP pc)	−1.3570	−1.7091	−1.5953	−1.6371	−1.7704	−3.4109
	(1.6012)	(1.3965)	(1.2656)	(1.3074)	(1.4973)	(5.4366)
log(Human capital)	−0.4720	0.9049	1.0892	1.0898	0.7934	−15.0338
	(4.7243)	(5.8607)	(6.0388)	(5.9583)	(5.6801)	(10.4157)
Population age	−1.3260***	−1.0504***	−1.0746***	−1.0459**	−1.0222**	0.0341
	(0.2425)	(0.3850)	(0.3786)	(0.3943)	(0.4154)	(0.2189)
Internet use	−0.0491***	−0.0209	−0.0235	−0.0218	−0.0191	0.3004
	(0.0138)	(0.0183)	(0.0179)	(0.0185)	(0.0201)	(0.3329)
Agriculture share	−1.6384	−3.6590	−3.6350	−3.7208	−3.6826	−9.4123**
	(3.5228)	(2.7024)	(2.6559)	(2.6752)	(2.7193)	(4.4520)
Industry share	−1.9414	−1.6989	−1.7727	−1.6176	−1.5936	−8.4439
	(2.3214)	(1.8857)	(1.8893)	(1.8266)	(1.8328)	(6.1364)
Unemployment	2.5690	4.0009**	4.2710**	3.8831**	3.6581*	−9.9263
	(1.7050)	(1.7910)	(1.8426)	(1.8943)	(2.0584)	(17.3790)
Intercept	110.6483***	94.3827***	93.7550***	93.2524***.	94.3099***	77.6795
	(15.2740)	(25.7926)	(25.6341)	(25.8544)	(26.2153)	(72.4819)
N	239	239	239	239	239	239
R^2 within	0.8976	0.9313	0.9312	0.9312	0.9310	
F	175.3280***	132.4761***	129.3655***	129.4507***	136.2400***	3222.8421***
Cragg-Donald F stat					53.1150	
Stock-Yogo (10%)					16.3800	
Stock-Yogo (15%)					8.9600	
Stock-Yogo (20%)					6.6600	
Arellano–Bond test for AR(2) [p-value]						−0.25 [0.800]
Hansen test of overid restrictions [p-value]						3.00 [0.809]
Fixed effects	Yes	Yes	Yes	Yes	Yes	
Time effects	No	Yes	Yes	Yes	Yes	Yes

Notes: In Model 5, the instrument is the lag of branches.
Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

other way around, then suggesting that the link is rather weak. This idea is supported by Fig. 2. The scatter plot shows a negative relationship between branches and the Gini index, in line with the theoretical predictions, yet it is not strong. In fact, the Pearson correlation, despite being significant, reaches only −0.19.

These descriptive statistics only offer preliminary evidence on the branches—inequality link. In order to test the relationship in a formal framework the following model is estimated:

$$Gini_{it} = \alpha_i + \beta Branches_{it} + \gamma C_{it} + \varepsilon_{it} \tag{1}$$

where $Gini$ and $Branches$ have been previously described, C is a vector of the control variables defined above and ε is the error term. Subscripts i and t refer to region and year, respectively, and α, β, and γ are model parameters.

The baseline estimations are conformed by two-way panel fixed-effects models. In order to deal with a potential problem of endogeneity, several strategies are implemented. On the one hand, a potential source of endogeneity might be reverse causality. In that regard, a causal link running from income inequality to branches per capita lacks from theoretical support. It is not obvious why banks should condition their branch closures decisions on the inequality levels and how that strategy could be aligned to their business objectives. Another potential source of endogeneity is omitted variables. In order to reduce that problem as much as possible, apart from considering several control variables—some of them as important as GDP per capita or credit per capita, the models include province and time fixed effects. The latter can be particularly relevant for our context. The reason is that information as important as FinTech development and use of online banking is not available at the province level. Control variables such as the

Table 3
Results for different types of bank.

	Dependent variable: Gini index					
	Model 1 (OLS)	Model 2 (OLS)	Model 3 (OLS)	Model 4 (OLS)	Model 5 (OLS)	Model 6 (OLS)
Commercial bank branches	−0.0198					
	(0.0154)					
Saving bank branches		0.0030				
		(0.0098)				
Cooperative bank branches			−0.0199			
			(0.0260)			
Commercial bank branches growth				0.0667		
				(0.1974)		
Saving bank branches growth					0.1850	
					(0.3714)	
Cooperative bank branches growth						0.0420
						(0.1594)
Credit per capita	0.0369	0.0355	0.0379	0.0358	0.0360	0.0366
	(0.0264)	(0.0258)	(0.0269)	(0.0261)	(0.0258)	(0.0263)
Population growth	−22.0264**	−21.4640**	−22.6648**	−21.8014**	−21.1788*	−21.4987**
	(10.1886)	(10.4023)	(10.3535)	(10.1881)	(10.6987)	(10.3649)
Population density	−0.0148	−0.0167	−0.0157	−0.0170	−0.0169	−0.0166
	(0.0106)	(0.0107)	(0.0111)	(0.0106)	(0.0106)	(0.0108)
log(GDP pc)	−1.6361	−1.6106	−1.6307	−1.6454	−1.5918	−1.6382
	(1.2762)	(1.3076)	(1.2931)	(1.2778)	(1.2749)	(1.2796)
log(Human capital)	0.8948	1.0666	1.0733	1.0972	0.9479	1.0647
	(5.8517)	(6.0119)	(6.0923)	(6.0499)	(6.0157)	(6.0207)
Population age	−0.9671**	−1.0748***	−1.0633***	−1.0880***	−1.0686***	−1.0864***
	(0.3779)	(0.3772)	(0.3831)	(0.3765)	(0.3822)	(0.3787)
Internet use	−0.0228	−0.0237	−0.0237	−0.0230	−0.0229	−0.0232
	(0.0182)	(0.0186)	(0.0185)	(0.0183)	(0.0182)	(0.0185)
Agriculture share	−3.6364	−3.6184	−3.6059	−3.6086	−3.6808	−3.6249
	(2.6800)	(2.6756)	(2.6877)	(2.6654)	(2.6427)	(2.6994)
Industry share	−1.7628	−1.8480	−1.7592	−1.8130	−1.8067	−1.8379
	(1.9604)	(1.8885)	(1.9282)	(1.8899)	(1.9127)	(1.8976)
Unemployment	3.9773**	4.4520**	4.2000**	4.3867**	4.3581**	4.4092**
	(1.8332)	(1.8021)	(1.7930)	(1.8329)	(1.8106)	(1.8157)
Intercept	90.0416***	93.7078***	93.6136***	94.6433***	93.6165***	94.5260***
	(24.4784)	(25.6645)	(26.0188)	(25.4025)	(25.5989)	(25.5693)
N	239	239	239	239	239	239
R^2 within	0.9317	0.9310	0.9311	0.9310	0.9310	0.9310
F	138.1282***	138.8817***	133.6719***	128.4414***	130.2428***	127.8065***
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

average age of population and the share of internet users can partially capture that, but they are imperfect proxies. Time effects can well complement them and better control for that phenomenon.

Besides these considerations, the baseline estimations are complemented by IV estimations. Obtaining an appropriate instrument for branches is a challenging issue, particularly in a panel setting for which temporal variability in the instrument is needed. We provide two alternative scenarios. In the first one, a 2SLS model is run using the lagged value of *Branches* as instrument. This is a common strategy when external instruments are scant and/or lack robustness. In the second one, the model is estimated using the Generalized Methods of Moments (GMM Arellano–Bond) estimator, which is also a popular alternative to the use of external instruments.

3. Results

The results of the baseline estimations are contained in the first two columns (Models 1 and 2) of Table 2. In the first case, time effects are not included, whereas in the second they are present. The coefficient of bank branches is negative for the first case, in line with the theory and previous evidence for other contexts, but it turns non-significant when time effects are included. Our models do not account explicitly for alternative forms of banking relying on digitalization, but time effects might be capturing the substantial increase in online banking penetration, which is taking place at the same time that branch density is reducing. This might be one of the potential drivers of the loss of significance of branches after the inclusion of time effects. Apart from that, population growth and population age are variables that reduce inequality, whereas unemployment increases it.

Table 4
Results for alternative scenarios.

	Dependent variable: Gini index			
	Gini index		Branches	
	Model 1(OLS)	Model 2 (OLS)	Model 3 (OLS)	Model 4 (OLS)
	Below median	Above median	Below median	Above median
Branches	−0.0166	0.0007	−0.0095	−0.0005
	(0.0131)	(0.0174)	(0.0266)	(0.0174)
Credit per capita	0.0219	0.0318	0.0165	−0.0025
	(0.0314)	(0.0308)	(0.0388)	(0.0298)
Population growth	−45.8777***	7.4084	−13.8724	−36.1066**
	(11.7043)	(12.4894)	(14.7373)	(15.0491)
Population density	−0.0619**	−0.0074	−0.0080	−0.0381
	(0.0254)	(0.0113)	(0.0159)	(0.0515)
log(GDP pc)	−0.9346	−2.1941*	−2.7593	−0.4378
	(1.0530)	(1.1163)	(2.3097)	(1.3521)
log(Human capital)	−2.7204	1.1749	−2.8125	−5.5912
	(4.1644)	(6.3235)	(7.9204)	(5.5969)
Population age	−1.8489***	0.2684	−0.6576	−1.3942***
	(0.2763)	(0.5202)	(0.7330)	(0.3484)
Internet use	−0.0377*	−0.0139	−0.0112	−0.0077
	(0.0197)	(0.0203)	(0.0444)	(0.0203)
Agriculture share	−6.4378**	−0.7823	2.2690	−7.3790**
	(2.6214)	(2.7964)	(4.2761)	(2.7376)
Industry share	−1.0607	2.3062	−6.7657*	1.6451
	(1.4077)	(2.5078)	(3.2917)	(1.5870)
Unemployment	0.4273	8.8260***	8.0436**	−0.0421
	(1.5072)	(2.2556)	(3.2012)	(1.6787)
Intercept	138.7123***	38.9375	95.1357**	111.9892***
	(18.5810)	(30.9821)	(39.6431)	(26.0197)
N	120	119	121	118
R^2 within	0.9584	0.9657	0.9444	0.9425
F	986.6589***	232.9454***	267.1549***	144.6479***
Fixed effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

We also analyze whether there is an impact associated to yearly variations in branch density (Model 3). The results for the variation of branches are non-significant, showing that closures (variations are always negative for all provinces and years) are not having a significant impact on income inequality after the rest of controls and both fixed and time effects are taken into account. Moreover, in Model 4 we use the lag of branch density instead of contemporaneous levels to test whether there might be a delay in the impact that is not being captured using current data. The results for this estimation are consistent with our previous models, showing a non-significant coefficient for the lag of branches.

The other two columns (Models 5 and 6) report IV estimations, in which *Branches* is treated as endogenous. In Model 5, *Branches* is instrumented with its lagged value as instrument. The results yield again a non-significant effect for branch density. The Cragg-Donald statistic is far above the critical value of the Stock-Yogo for the most restrictive scenario of 10% bias, thus giving support to the validity of the instrument. Finally, the GMM Arellano–Bond estimation (Model 6) corroborates the previous results. The GMM equation is properly specified, as suggested by the second order autocorrelation and the Hansen test of over-identification, which are both non-significant. Then, the estimations show that the preliminary evidence of a negative link between branch density and income inequality showed by the descriptive statistics is not supported when including control variables and a panel structure, particularly when time effects are considered.

Apart from the baseline estimations, we provide results for alternative scenarios. Following Minetti et al. (2021), and Peruzzi et al. (2023) who found that cooperative banks play a more relevant role in the reduction of inequality, we report results by type of bank, distinguishing between commercial, saving and cooperative banks. Whereas commercial banks have been traditionally more oriented to market profitability, saving banks and cooperative banks have a more local orientation and their business models rely more on relationship banking, thus having comparative advantages in funding less transparent borrowers. The results are reported in Table 3, including estimations in levels (Models 1 to 3) and in variations (Models 4 to 6). In all cases, the coefficients are non-significant, being the results not aligned to Minetti et al.' (2021) and Peruzzi et al.'s (2023) findings. The results for the control variables are in line with the baseline estimations.

Finally, Table 4 reports estimations for provinces below and above the median of both the Gini index (Models 1 and 2) and bank branch density (Models 3 and 4) to control for possible non-linear effects. The results again support the baseline estimations, showing a non-significant effect of branches for all the scenarios. Therefore, the hypothesis that a higher branch density reduces inequality is not supported for the Spanish provinces.

4. Conclusions

This paper provides some evidence on the impact of bank branches on income inequality in the Spanish provinces in the post-crisis period. Spain is the country that has experienced the largest number of branch closures in the Euro area, yet the impact of the restructuring process and how a reduced branch density is affecting inequality levels is underexplored. For a short panel of four years, the results suggest that differences in bank branch density do not affect income inequality levels in the Spanish provinces. Then, our results are not aligned to the theoretical predictions and to previous contributions for other contexts. There are several reasons that can explain our findings but, first of all, it is important to highlight that our results do not aim to be generalizable to all contexts, but to better understand the Spanish subnational reality in terms of inequality and the role played by branch density.

Among the potential explanations for our findings, it could be that the effects of closures are not immediate but will be noticeable in the coming years. Another reason might be an excessive number of branches before the restructuring process. Then, the current number of branches may still be sufficient to guarantee access to financial services. Moreover, people might actually access financial services through online channels. In contrast to most of the previous literature analyzing this issue, this study has considered a recent period in which new technologies are far more widespread and accessible than only a few years ago, and alternative forms of banking based on digital technologies are emerging. In such context, most people would be actually not financially excluded, and branches would become less important. Unfortunately, data on these latter aspects are still nonexistent for the subnational level, especially for the most disaggregated geographical areas such as NUTS-3 units. The improvement of the current databases and the consideration of longer periods–our four-year period could actually be a limitation–might confirm these hypotheses in the coming years. Also, future research initiatives might consider regions from different countries, which would definitely help to make results more generalizable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.The authors do not have any conflict of interest.

Data availability

Data will be made available on request.

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